Waste Management 79 (2018) 781–790

Contents lists available at ScienceDirect

Waste Management

journal homepage: www.elsevier.com/locate/wasman

Estimation of the generation rate of different types of plastic wastes and possible revenue recovery from informal recycling

Atul Kumar, S.R. Samadder *, Nitin Kumar, Chandrakant Singh

Department of Environmental Science & Engineering, Indian Institute of Technology (Indian School of Mines), Dhanbad 826004, India

ARTICLE INFO

Article history:
Received 18 May 2018
Revised 1 August 2018
Accepted 27 August 2018
Available online 1 September 2018

Keywords:
Informal
Machine learning models
Plastic waste
Recycling
Revenue generation
Socioeconomic groups

ABSTRACT

Plastic waste generation is an inevitable product of human activities, however its management faces challenges in many cities. Understanding the existing patterns of plastic waste generation and recycling is essential for effective management planning. The present study established a relationship between plastic waste generation rate and the identified socioeconomic groups, higher socioeconomic group (HSEG), middle socioeconomic group (MSEG), and lower socioeconomic group (LSEG) of the study area (Dhanbad, India). For identification of the socioeconomic groups, four different socioeconomic parameters were considered (total family income, education, occupation and type of houses). The information related to the identified parameters were obtained using questionnaire survey conducted in the selected households. One week plastic waste sampling was carried out in the households of all the socioeconomic groups. The plastic waste generated in the study area was 5.7% of the total municipal solid waste. In terms of total plastic waste generation rate, it was found that HSEG had maximum (51 g/c/d) and LSEG had minimum (8 g/c/d) generation rate. The present study area does not have any formal waste recycling system. Thus, the amount of plastic waste recovered and the revenue generated from recycling of plastic waste by the active informal recyclers (waste pickers, itinerant waste buyers and scrap dealers) in the study area have been evaluated. Additionally, three non-linear machine learning models i.e., artificial neural network (ANN), support vector machine (SVM) and random forest (RF) have been developed and compared for the prediction of plastic waste generation rate.

© 2018 Elsevier Ltd. All rights reserved.

1. Introduction

Various types of plastic products have become an indispensable part of lifestyle. Plastic production has increased tremendously in past 50 years. In India, approximately 12 million tonnes of plastic products are used annually and 70% of them is disposed of indiscriminately as waste (Singh et al., 2017). India being one of the fastest growing plastic market, has an annual plastic production growth rate of 16%, followed by 10% per annum for China and 2.5% per annum for UK (BPF, 2012). With such a high production rate, an established waste processing route for its recycling and recovery is necessary. Unlike the developed countries, recovery of plastic waste remains mostly an informal activity in the developing countries like India. Informal sector include unregulated and unregistered individuals or groups such as waste pickers, scavengers, itinerant waste buyers (IWBs) and scrap dealers involved in recycling of waste materials. In most of the Indian cities, the waste segregation and identification for potential recyclable items are carried out by informal sector (Nzeadibe, 2009; Nandy et al., 2015). Government of India has provided a few regulatory framework (such as Solid Waste Management Rules, 2016 and Plastic Waste Management Rules, 2016) for the management of waste generated in the country. As per the Solid Waste Management Rules, 2016 the state policies and strategies should acknowledge the contribution of the informal sector for waste recycling. For effective management of plastic waste in particular, Government of India has notified Plastic Waste Management Rules, 2016 that

Abbreviations: ANN, artificial neural network; ASTM, American Standard for Testing Material; CD, compact disc; CPCB, Central Pollution Control Board; DMC, Dhanbad Municipal Corporation; GDP, gross domestic product; HDPE, high density polyethylene; HSEG, higher socioeconomic group; INR, Indian Rupees; IWB, itinerant waste buyer; LDPE, low density polyethylene; LSEG, lower socioeconomic group; MAPE, mean absolute percentage error; MLR, multiple linear regression; MoEFCC, Ministry of Environment Forest and Climate Change; MSEG, middle socioeconomic group; MSW, municipal solid waste; PC, polycarbonate; PET, polyethylene terephthalate; PP, polypropylene; PS, polystyrene; PU, polyurethane; PVC, poly vinyl chloride; R^2, coefficient of determination; RF, random forest; RMSE, root mean square error; SVM, support vector machine; UK, United Kingdom; US, United States; USA, United States of America.

* Corresponding author.
E-mail address: samadder@iitism.ac.in (S.R. Samadder).

https://doi.org/10.1016/j.wasman.2018.08.045
0956-053X/© 2018 Elsevier Ltd. All rights reserved.

contains some set regulations, laws, goals as well as roles and responsibilities of waste generator, Municipal Corporation, manufacturer, producer and importer of plastic waste. Through these rules, the Government of India aims to achieve the objective of clean India (a flagship program of Government of India). In India, identification, collection and recycling of plastic waste follow a hierarchy (as shown in Fig. 1), where waste pickers, scavengers and IWBs sell their scavenged items to scrap dealers. Small-scale exporters purchase sorted plastic wastes from scrap dealers. Ultimately, the exporters sell compacted plastic wastes to the industries for recycling and making new products (Sembiring and Nitivattananon, 2010). A certain amount (depending on the quantity and quality of the recyclable waste) is recovered by the involved service provider (scrap dealers, IWBs, etc.). Studies on the contribution of informal sector in plastic waste recycling in India is still lacking. Thus, quantification of material recovered by the informal sector remains a challenging task. In India, about 6.5 tonnes to 8.5 tonnes per day of plastic waste is collected by IWB's, scrap dealers, household waste collectors, etc. From this collected waste, about 50 to 80% of plastic waste is recycled (Nandy et al., 2015). A study conducted in one of the Indian cities in 2008 revealed that the earnings of waste pickers and scrap dealers were approximately US$ 24 and US$ 165 per month respectively from waste recycling (US$ 1 = INR 65; April 2018) (Zia et al., 2008). However, their earnings might have been increased up to two to three folds in last 10 years due to increase in generation, collection and price of recyclable wastes.

In order to know the quantity and composition of plastic waste and to reduce future generation, it is essential to understand how different factors are related to plastic waste generation. In the present study, plastic waste generation rate and composition have been evaluated based on the socioeconomic groups of the study area. The socioeconomic parameters considered for identification of the socioeconomic groups in the study area were education of head of the family, occupation of the head of the family, total family income and type of houses. The parameters considered for the present study have been widely used for the prediction of municipal solid waste (MSW), but not for the plastic waste generation prediction at city or municipality level. Income represents the consumption and waste generation pattern of any household. People with higher incomes would be expected to consume more packaged products and dispose larger quantities of plastic wastes (Emery et al., 2003). Education reflects the awareness among different socioeconomic groups from plastic waste related problems. Occupational status reflects the income and eventually the residents' willingness to pay for plastic waste collection services. Xiao et al. (2015) and Al-Khatib et al. (2015) also reported that the type of occupation of the head of a family was one of the main factors responsible for household waste generation rate because, it is expected to affect the awareness of the problems due to indiscriminate dumping of wastes. Previous research indicated that households' attitude towards recycling reflects from their socioeconomic status (Sidique et al., 2010).

Modeling methods are the most common techniques for plastic waste generation rate estimation at municipality and city level. Goel et al. (2017) categorised modeling methods into conventional and non-conventional methods. Conventional modeling methods includes sample survey (Thanh et al., 2010), multiple linear regression (MLR) (Kumar and Samadder, 2017), time series (Chung, 2010), system dynamics (Dyson and Chang, 2005), and geographical information system method (Purcell and Magette, 2009). Non-conventional methods are data-driven models such as artificial neural network (ANN) (Abdoli et al., 2012), random forest (RF) (Kannangara et al., 2018), support vector machines (SVM) (Abbasi et al., 2013), and fuzzy logic (Khan and Farooqi, 2012). All the modeling techniques have their own advantages and limitations. Conventional techniques are no longer effective due to heterogeneity in solid waste generation process (Abbasi et al., 2013). However, regression analysis is widely reported as an effective solid waste generation modeling technique, due to its simple algorithm and ability to identify influential parameters. But in order to comply with some stringent theoretical assumptions (such as, independency of input variables, normality of input variables and error term, constant variance), its applicability for complex problem is less. But, in recent years, models using machine learning approach (such as ANN, SVM and RF) has been gaining popularity (Abbasi and El Hanandeh, 2016). Machine learning techniques have high prediction ability and flexibility than MLR because, machine learning models work on complex non-linear data and are free from assumptions (Kannangara et al., 2018). In MLR technique, the relationship between independent and dependent variables is assumed to be linear and the interaction among independent variables must

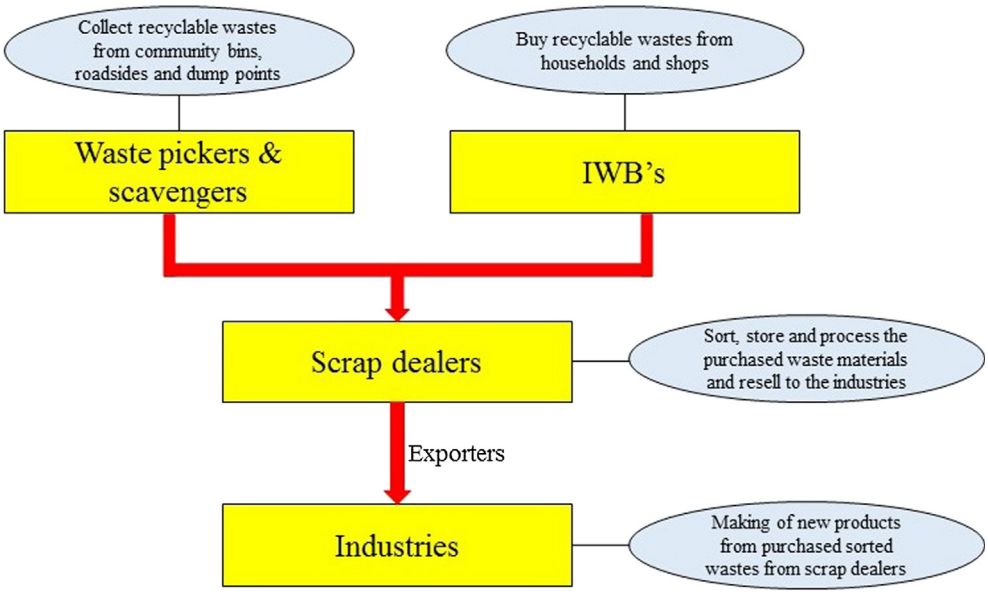
Collect recyclable wastes from community bins, roadsides and dump points
Buy recyclable wastes from households and shops
Waste pickers & scavengers
IWB's
Scrap dealers
Sort, store and process the purchased waste materials and resell to the industries
Exporters
Industries
Making of new products from purchased sorted wastes from scrap dealers

Fig. 1. Hierarchy of waste recycling by informal sectors.

be specified in advance. However, ANN requires no assumptions and the interaction among the independent variables are learned through an iterative process. In this study, three non-linear machine learning modeling techniques i.e., ANN, SVM and RF were compared for the prediction ability of plastic waste generation rate from households of Dhanbad Municipality.

Informal recyclers play a significant role in the city's plastic waste management. They not only earn livelihood for themselves, but also reduce the burden of local governments by diverting the recyclable plastic waste from landfills, thus rendering environmental and social benefits. The present study attempted to make an estimate of plastic waste collected and revenue generated by the active informal actors from plastic waste recycling. The study area is a part of one of the most populated cities of the state Jharkhand, India. Hence, this study will help the concerned authority in proper planning and management of plastic waste in the cities of similar socio-demographic profile.

2. Description of the study area

The present study area is a part of Dhanbad Municipality. Dhanbad is one of the major cities of the state Jharkhand and situated in the eastern part of India. It lies between 85°45′E to 86°30′E longitude and from 23°32′N to 24°5′N latitude. As per Census 2011, Indian cities have been grouped into different categories as per their population (Census of India, 2011). Dhanbad is a Class I city (supports more than 0.1 million population), which represents two-third of the total urban population of India. Dhanbad has a population of about 1.17 million, with a topographical coverage of 275 km^2 (Census of India, 2011). The responsible authority for collection and management of MSW of Dhanbad city is Dhanbad Municipal Corporation (DMC). DMC consists of 55 administrative wards and 11 such wards in main urban agglomerated area (Fig. 2) were chosen as the present study area that has an estimated population of about 0.25 million and approximately 40,000 households (Kumar and Samadder, 2017).

2.1. Present status of plastic waste management in the study area

The Municipal Corporation in the present study area (Dhanbad city) is mainly focusing on collection and disposal of the solid waste without segregation of wastes into a different types of wastes such as plastics, metals, glass, etc. Presently, the guidelines of Plastic Waste Management Rules, 2016 are not followed in the city for the collection and handling of plastic wastes (MoEFCC, 2016). Plastic waste is mainly collected by the waste pickers and IWBs. Waste pickers collect plastic waste from the community bins, transfer stations, and dump points located in the low-lying areas of the city. However, IWBs purchase plastics like polyethylene terephthalate (PET), high density polyethylene (HDPE) and low density polyethylene (LDPE) which have a resale value in the market mainly from households and shops. But the major problem for the city is the packaging plastic waste, which is neither being collected by the municipal authorities nor by the waste pickers or scrap dealers. These include plastic sachets, tobacco pouches, and the prohibited carry bags (with a thickness less than 50 μm), which are still available in the market and thus they remain unattended. A study conducted by Central Pollution Control Board (CPCB), Government of India in 2015 revealed that average daily plastic waste generation rate in Dhanbad was about 50.16 kg/tonne of MSW (CPCB, 2015). The finding revealed that approximately 69% of total plastic waste is composed of HDPE/LDPE materials.

3. Methodology

Present study has been divided into two sections. In the first section, paper questionnaire survey (with pre-selected questions)

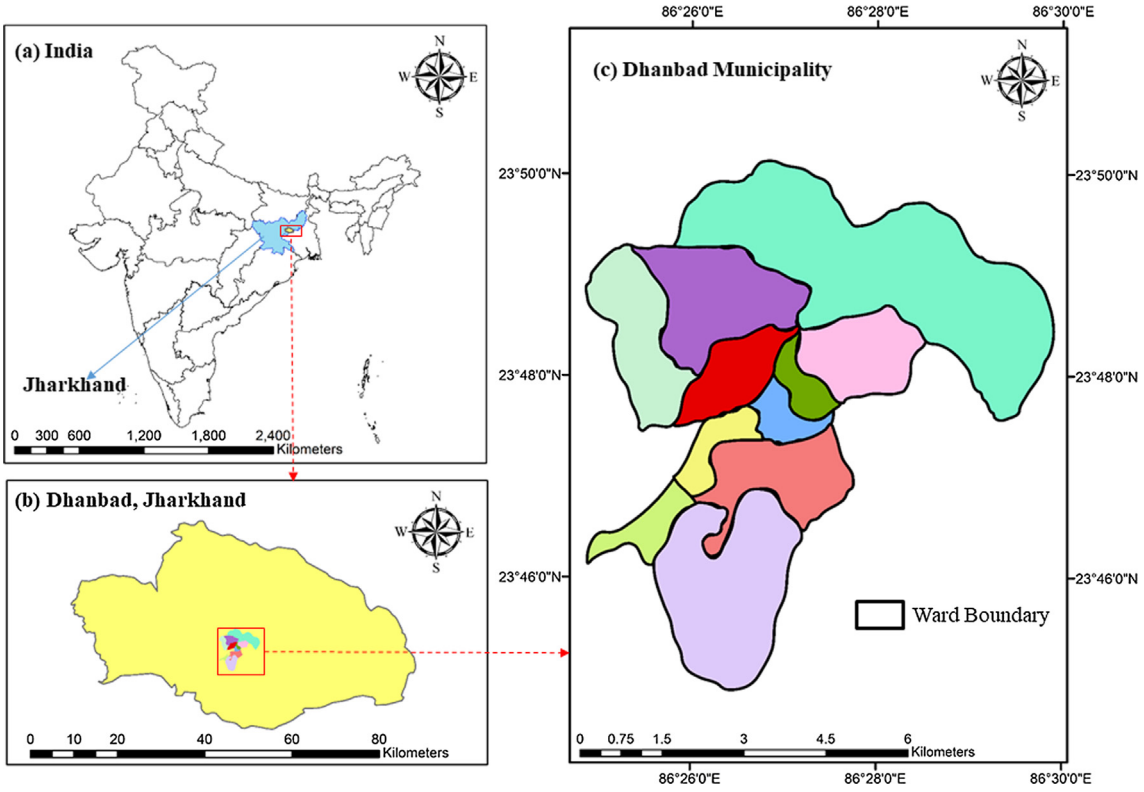

Fig. 2. Location of the study area.

was done in approximately 140 randomly selected households (stratified random sampling technique) of the study area. Based on outcome of the survey, different socioeconomic groups were identified. After that, waste sampling was done for one week from the selected households to get the estimates of plastic waste generation rate. Additionally, using the information from questionnaire and sampling data, machine learning models were developed and compared the prediction accuracy of plastic waste generation rate. In the second section, an estimate of revenue generation by the informal sector from plastic waste recycling in the study area has been presented.

3.1. Sample size estimation for household sampling

The sample size was estimated statistically using Eq. (1) (Mac Berthouex and Brown, 2002).

$$\text{Sample size}\,(n) = \left(\frac{z_{\alpha/2}\sigma}{E}\right)^2 \quad (1)$$

where n is the sample size for the study area, σ is the standard deviation, α is the level of significance (α = 0.05), z is the standard normal variate, and E is the confidence interval half-width.

3.2. Socioeconomic stratification of the sampled households and questionnaire survey

Identification and selection of socioeconomic parameters depend upon the nature of the study area and characteristic significance of the parameters. Previous studies had correlated numerous socioeconomic parameters such as gross domestic product (GDP), tourism activities, total consumer expenditure, recycling activities, and level of awareness with MSW characteristics (Ramachandra et al., 2018; Kumar and Samadder, 2017; Khan et al., 2016). But, the data related to most of the reported parameters are difficult to retrieve and not available or inadequate for the cities of developing countries. Therefore, parameters (whose data can be easily obtained) such as education of head of the family, occupation of head of the family, total family income and type of houses have been considered for the present study. The parameters were selected to depict the consumption and plastic waste generation pattern of the households. The parameter "education" was selected, because it is believed that level of awareness from waste related problems increases with increase in education level. The second parameter was "occupation", because occupational status reflects the academic achievements, income and decision making capability of the person, and control over the work and living environment. In this study, for the parameters "education" and "occupation", the maximum educational qualification acquired by head of the family and occupation of head of the family respectively have been considered. "Total family income" was another important parameter considered in several previous studies, because it reveals the consumption pattern of packaged and readymade products of any household. For the present study, income was stratified into five classes based on the annual income of the family (Table 1). Income class was classified based on the defined income group of United States (Pew Research Center, 2014). For conversion of the income class to the latest economic trends, GDP of USA and India was used. Income class for India was established using income class of USA in year 2016, as mentioned in Eq. (2).

$$Income\,(India, 2016) = Income\,(US, 2016) \times \frac{GDP_{2016}(India)}{GDP_{2016}(US)} \quad (2)$$

Another parameter is "type of houses" which had never been reported in previously published studies, but it has profound impact on the plastic and other type of waste generation rate. The houses in the present study were grouped into five different types (Table 1). The data related to these four parameters were obtained using the questionnaire survey conducted from each household (Beigl et al., 2008). The questionnaire was prepared based on the previous study by Khan et al. (2016), population demographics and consultation with Municipal Corporation staffs. The responses of questionnaire were obtained from the responsible person (or head of the family) of each household. The aim of questionnaire was to get information related to socioeconomic condition of households, type of houses and other information related to plastic waste management practices. The socioeconomic parameters considered for the present study were divided into different levels as shown in Table 1. The households were then categorised into three different socioeconomic groups (LSEG, MSEG and HSEG) based on the outcomes of questionnaire and stratification methods used by Khan et al. (2016). Khan et al. (2016) assigned weighted scores to the different levels of each of the parameters, then the score of each parameter was added for every household. In the present study, same methodology was adopted, where the added scores of each households were divided into three different ranges in which higher, medium and lower ranges show three different socioeconomic groups, i.e., HSEG, MSEG and LSEG respectively. A total of 120 households were selected out of 140 surveyed households and found to be sufficient to represent all the three socioeconomic groups of the present study area (Table 2). In a similar type of study, Thanh et al. (2010) considered a sample size of 130 households for estimating the plastic waste generation in Can Tho City, Vietnam.

Table 1
Description of the different socioeconomic parameters considered for stratification of socioeconomic groups.

S. No.	Education	Occupation	Total annual family income (in US$)	Type of houses
1	Professional and Doctorate	Professionals/Experts	24,524	Bungalows, Mansions
2	Masters/Bachelor's Degree	Semi-Professionals	16,350–24,524	Flats (with at least 3 rooms and storage)
3	Secondary/Senior Secondary Education	Farmers/clerk	5451–16,349	Flats (with at most 2 rooms)
4	Primary Education (read and write)	Skilled workers	4087–5450	Single room quarters
5	Illiterate	Labour class/daily wagers	Below 4087	Shanty, houses with earthen floors

Table 2
Plastic waste generation rate and recycling/recovery of plastic waste in different socioeconomic groups.

S. No.	Socioeconomic groups	No of sampled households	Plastic waste generation rate (g/c/d)	Plastic waste recovery (%)
1	HSEG	40	51	67
2	MSEG	40	27	93
3	LSEG	40	8	44

3.3. Sample collection from different socioeconomic groups

Sampling was done for complete one week to evaluate the quantity and composition of plastic wastes generated by the selected households (40 households of each socioeconomic group). A sampling bag was provided to each of the selected households. The respondents of the households were asked to store their generated plastic wastes over a period of 24 h in the provided bags. These bags were collected the next day and a new bag was provided to the respondents for next day collection. The sampled plastic wastes generated from each household were washed and air dried in an open space. This waste was then segregated according to different plastic types as provided by CPCB (2015). The air dried and segregated plastic wastes were weighed using an electronic weighing balance and data was recorded for the respective household.

Finally, the assessment and quantification of different types of plastic waste generated from all sectors (residential, commercial, marketplace and institutional) of the study area were carried out. For this, a complete one day monitoring and sampling was done at transfer station. In the study area, during daytime tractor trolleys are used to carry wastes from community bins, market place and other commercial and institutional establishments to the transfer station. The collected wastes are then transported to the landfill using trucks. In the present study, ASTM Method (D5231-92) was used for the assessment and quantification of plastic waste. For this, 1 tonne of thoroughly mixed MSW arrived at transfer station was considered. The 1 tonne of mixed MSW was reduced to 125 kg using coning and quartering technique. Different types of plastic wastes were then segregated and quantified from the reduced 125 kg of mixed MSW.

3.4. Model development

Modeling is one of the main and reliable techniques for estimating the waste quantity. In this study, machine learning approach has been considered for the prediction of plastic waste generation rate, because it has better prognostic abilities than regression technique (Kannangara et al., 2018). In the present study, three non-parametric machine learning techniques were used and compared for prediction of plastic waste generation rate. k-fold cross validation technique was used for accuracy assessment using statistical metrics such as Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE) and coefficient of determination (R^2). For this study, four parameters namely income, education, occupation, type of houses were used as independent variables and plastic waste generation rate was used as dependent variable.

3.4.1. Machine learning algorithms

In the present study, plastic waste generation rate was predicted using three machine leaning techniques, ANN, SVM and RF. The simulations of ANN are based on complex biological functioning of the human brain. The structure of an ANN model consists of an input layer, one or more hidden layers and an output layer. For the present study, ANN was optimized at one hidden layer containing five neurons with a logistic activation function. The number of hidden layers, neurons and their activation function for optimal neural network were determined using trial and error method (Azadi and Karimi-Jashni, 2016) through multiple runs of R statistical software package. Unlike ANN, which is basically a black box model, SVM had proved to be quite efficient when dealing with small sample size. SVM algorithm creates optimal decision hyper planes from the training dataset based on the user defined kernel across which the support vectors derived from the training datasets are tested. The distance of support vectors from the hyper plane defines the efficacy of the datasets. For the present study, the linear kernel of SVM was also optimized through multiple runs of R software. RF algorithm uses a tree based learning model (also known as decision trees). Each decision predicted by the model is further split into several nodes. The performance of RF model is thus dependent on development of several small decision trees. RF is structured after three major parameters: (i) ntree, defining the total number of decision tree to be constructed; (ii) mtry, defining total number of prediction splits at each node and; (iii) nodesize, is the least size of terminal node at each decision tree. For the present study, RF was tuned at ntree, mtry and nodesize value of 100, 5 and 5 respectively. RF model was also optimized based on several trial runs of R software. The RF model runs till the optimized parameters are satisfied. Recent studies discussed a similar decision based tree model for MSW generation prediction (Kannangara et al., 2018).

3.4.2. Model validation

K-fold cross validation technique was used for training and testing of the developed models. In k-fold cross validation, the original dataset is divided into k sub-datasets of equal size. Out of k subsets, k-1 subsets are utilized for training of model and remaining for testing the model. The technique is repeated k times such that all the datasets are utilized as either training or testing dataset. For the present study, 5-fold cross validation technique was used for model training and testing. In which, 4 subsets were utilized as training and remaining as testing dataset. The process was repeated 5 times for cross-validation. There are several techniques available that can be used for the model performance evaluation. In the present study, the performance of the model was assessed using three different statistical metrics i.e., MAPE, RMSE and R^2 as mentioned in Eqs. (3), (4) and (5) respectively (Kannangara et al., 2018).

$$\textit{Mean Absolute Percentage Error}\ (MAPE) = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{Y_i - \widehat{Y}_i}{Y_i}\right| \tag{3}$$

$$\textit{Root Mean Square Error}\ (RMSE) = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\widehat{Y}_i - Y_i\right)^2} \tag{4}$$

$$\textit{Coefficient of Determination}\ \left(R^2\right) = 1 - \frac{\sum_{i=1}^{n}\left(\widehat{Y}_i - Y_i\right)^2}{\sum_{i=1}^{n}\left(Y_i - \bar{Y}\right)^2} \tag{5}$$

where Y_i and $\widehat{Y}_i$ are the observed and predicted value of plastic waste generation rate, $\bar{Y}$ is the sample mean of observed plastic waste generation rate data and n is the number of observations.

3.5. Recovery and revenue generation from plastic waste

For the purpose of recovery analysis, field visits to temporary dump sites/transfer stations, market places, landfills and residences of the people involved in the process were done. It should be noted that there is no exact estimation of the total number of informal recyclers active in the study area. Therefore, to understand the plastic waste recovery scenario, a questionnaire guided interview was carried out with some of the actors (waste pickers, IWB's and scrap dealers). This included 45 waste pickers, 15 IWB's and 4 scrap dealers (2 each from small and large scrap dealers), which were randomly selected in the study area. The whole methodology was an attempt to estimate the quantity and revenue recovered from plastic waste recycling by informal recyclers. Identification, collection and dealing pattern of various actors involved

were evaluated. This involved the segregation of recoverable materials from MSW (such as metals, plastics, glass, etc.). Questionnaire guided interviews were conducted to get the information related to the quantity and revenue generated (per day) from different plastic materials by waste pickers, IWB's and scrap dealers. The data obtained was recorded to determine average revenue generated by involved actors in case of plastic waste. This data was also compared with the previous studies related to plastic waste recycling, recovery and revenue generation.

4. Results and discussion

4.1. Plastic waste generation potential by various socioeconomic groups

The most common application of plastic is in packaging of products, which accounts for approximately 40% of the total plastic use (Nandy et al., 2015). Most of the packaging plastic gets discarded after single use. Plastic waste obtained from various sampled households was analysed. The share of plastic waste was found to be 14%, 9% and 3% of the total MSW in the households of HSEG, MSEG and LSEG respectively. It was found that HSEG had the highest plastic waste generation rate (51 g/c/d), followed by MSEG and LSEG with a generation rate of 27 g/c/d and 8 g/c/d respectively (Table 2). The plastic waste generation rate in HSEG was much higher than MSEG and LSEG because, HSEG people have tendency to use packaged products (packaged foods, water bottles, milk pouches, etc.) in their households. In terms of total plastic waste generation (% by weight) from different socioeconomic groups in the study area, the share of HSEG was maximum (54%), whereas for MSEG and LSEG, it was 34% and 12% respectively (Fig. 3). Many research findings pointed out that plastic waste generation was more in HSEG and in the families having high income (Khan et al., 2016; Monavari et al., 2012). At the same time, a few researchers have reported that income is not directly related to plastic waste generation; similarly Al-Khatib et al. (2015) reported that income levels do not show a strong relationship to awareness levels of waste related problems.

4.2. Relationship between socioeconomic groups and plastic waste generation rate

The plastic waste was categorised into different types as per the classification method of CPCB (2015) (Table 3). The generation rate of different types of plastic waste from the households of different socioeconomic groups has been shown in Fig. 4. Among all the socioeconomic groups, HSEG had the maximum plastic waste

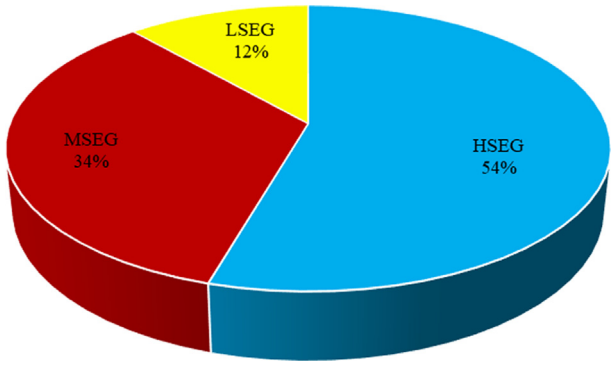

Fig. 3. Contribution of various socioeconomic groups on plastic waste generation.

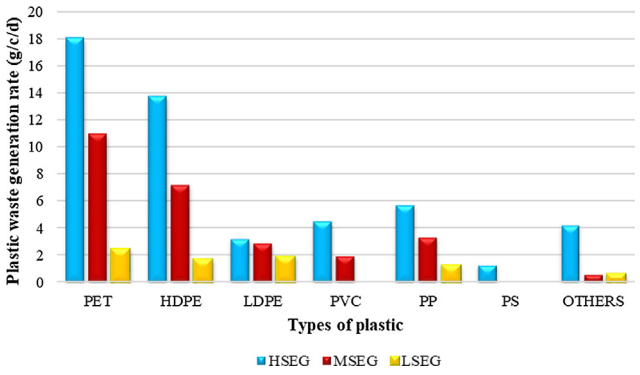

Fig. 4. Generation rate of different types of plastic wastes by various socioeconomic groups.

Table 3
Physical classification of plastic waste and their generation rate in the study area.

S. No.	Source code	Name of plastics	Applications	Current generation rate (kg/tonne of MSW)
1	1	Polyethylene terephthalate (PET)	Drinking water bottles, soft drink bottles, food jars, jell and pickles jars, plastics films, sheets	7.702
2	2	High density polyethylene (HDPE),	Shopping bags, food containers, woven sacks, bottles, plastics toys, milk pouches, detergent bags, metalized pouches	30.650
3	3	Polyvinyl chloride (PVC)	Pipes, hoses, sheets, wire, cable insulations, multilayer tubes	0.506
4	4	Low density polyethylene (LDPE)	Plastic bags, various containers, dispensing bottles, wash bottles, tubing	9.948
5	5	Polypropylene (PP)	Disposable cups, bottle caps, straws	5.649
6	6	Polystyrene (PS)	Disposable cups, glasses, plates, spoons, trays, CD covers, cassette boxes, foams	1.084
7	7	Thermoset, polycarbonate (PC), Polyurethane (PU)	CD, melamine plates, helmets, shoe soles.	1.365
Total generation of plastic waste				56.904

generation rate in all the types (Fig. 4), due to small family size and tendency of using packaged items. PET (drinking water bottles, soft drink bottles, food jars, pickle jars, plastic films & sheets) was found as the maximum generated plastic waste type from households of all the socioeconomic groups with generation rate of 18.04, 11.02 and 2.46 g/c/d for HSEG, MSEG and LSEG respectively (Fig. 4). This was followed by HDPE, which includes carry bags, food containers, woven sacks, plastic toys and milk pouches. In the present study area, all types of plastic wastes were found in the waste stream of HSEG, whereas polyvinyl chloride (PVC) and polystyrene (PS) were absent in plastic waste collected from LSEG (Fig. 4).

4.3. Estimation of plastic waste generation rate

The household plastic waste generation rate was estimated using three different machine learning techniques (ANN, SVM and RF). k-fold cross validation technique was used for training and testing of the developed models. Advantage of such technique is that it eliminates the chances of any biased prediction due to uneven distribution of training and testing datasets. k-fold cross validation technique divides the dataset into k subsets and each of the subsets are used separately for training and testing of the model. For the present study, 5-fold cross validation technique was used for model development and testing. In this, the dataset of 120 households was divided into 5 subsets, each containing 24 individual household plastic waste generation rate. The technique was repeated 5 times to utilize each training and testing dataset for model development. Model accuracy was assessed using the statistical metric and it was observed that ANN (RMSE = 9.53 g/c/d, MAPE = 34.07%, and $R^2 = 0.75$) performed slightly better than SVM (RMSE = 9.88 g/c/d, MAPE = 40.65%, and $R^2 = 0.74$) and RF (RMSE = 11.22 g/c/d, MAPE = 43.57%, and $R^2 = 0.66$) for the prediction of plastic waste generation rate (Table 4). Fig. 5 shows the observed and predicted plastic waste generation rate using three different models. The variation in the performance of the developed models is due to the use of different prediction algorithms. Fig. 6 shows the comparison of the observed plastic waste generation rate with the predicted plastic waste generation rate using ANN, SVM and RF models. It can be observed that the predicted values from the models are closer to the observed values, however the prediction accuracy of ANN ($R^2 = 0.75$) was better than SVM ($R^2 = 0.74$) and RF model ($R^2 = 0.66$).

Table 4
Accuracy assessment of the ANN, SVM and RF models for prediction of plastic waste generation rate in the study area.

Models	Statistical metrics		
	RMSE	MAPE	R^2
ANN	9.53	34.07	0.75
SVM	9.88	40.65	0.74
RF	11.22	43.57	0.66

4.4. Recycling and recovery of plastic waste

During questionnaire survey, the respondents claimed that they recycle only some fraction of plastic waste such as broken plastic chairs, buckets, durable plastic carry bags, bottles, etc., which can be either reused or have some significant resale value. However,

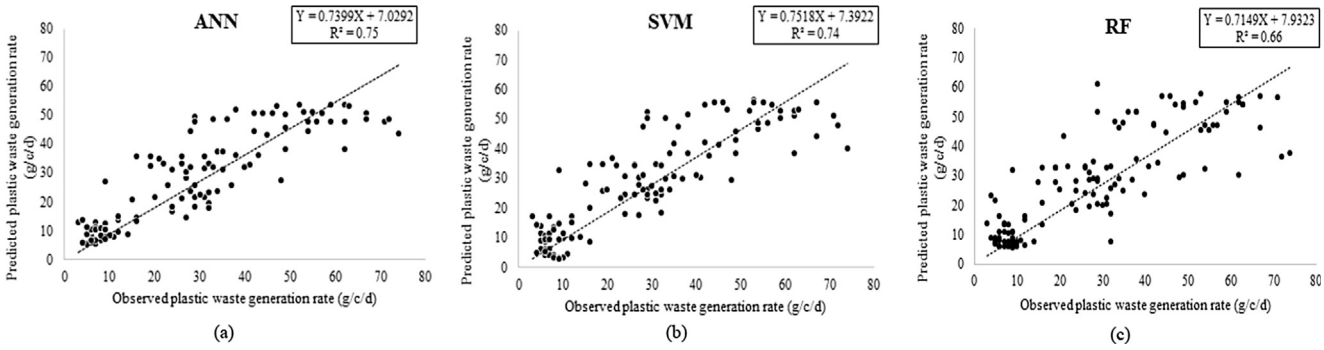

Fig. 5. Scatter plot of the observed and predicted plastic waste generation rates using (a) ANN, (b) SVM and (c) RF.

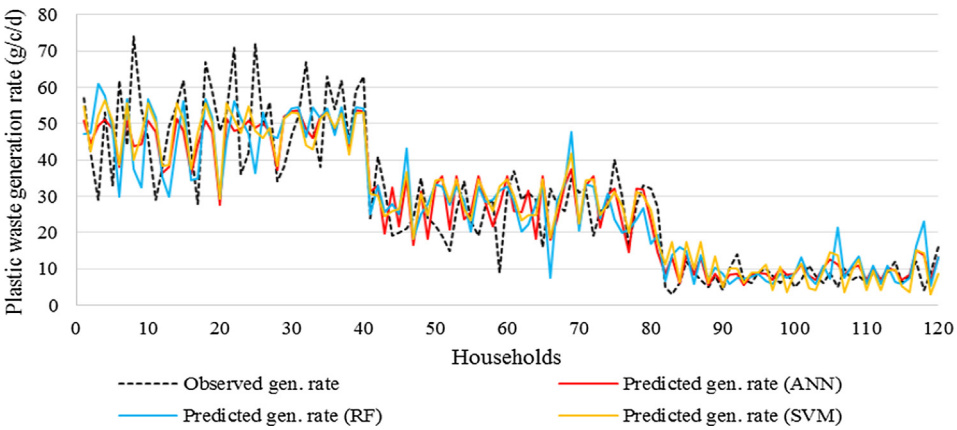

Fig. 6. Comparison of the observed and predicted plastic waste generation rate with the estimated machine learning models using ANN, SVM and RF.

most of the packaging plastic and polyethylene bags are discarded after single use. In an attempt to assess the plastic waste management practices by different socioeconomic groups, the observation was made using the waste sampling data and the responses received during questionnaire survey regarding recycling and recovery practices. Table 2 shows that recycling and recovery of plastic waste was highly practiced by MSEG (93%) (Table 2). It was observed that MSEG people have tendency to sell their generated plastic waste to IWB's for some revenue generation. Plastic waste generation rate as well as recycling and recovery percentage was minimum for LSEG (44%) among all the socioeconomic groups (as mentioned in Table 2). Though, the LSEG were also involved in the recovery of plastic waste for revenue generation, but due to the lack of awareness about recycling of plastic, they reject some of the recyclable plastic waste along with other wastes. For HSEG, recycling and recovery of plastic waste was not on par with generation rate (Table 2). The lesser percentage of recycling activities were observed in HSEG (67%) as compared to MSEG, because they feel that reselling of plastic waste does not fetch significant revenue. Therefore, it was observed that price of recyclable plastic waste is apparently the primary motivation for households' recycling activities.

4.5. Generation rate of different types of plastic wastes in the study area

The plastic waste coming to the transfer station from different parts (residential, commercial, marketplace and institutional) of the study area was segregated and quantified (as shown in Table 3). It was observed that the packaging plastic waste was the most predominant in the plastic waste stream at transfer station. HDPE had maximum (30.65 kg/tonne of MSW) contribution to the total plastic waste generation rate in the study area. HDPE, LDPE and polypropylene (PP) are the three most commonly used packaging plastic & carry bags materials that are available at low cost and found in the plastic waste stream (Das and Tiwari, 2018). In this study also HDPE, LDPE and PP were major components of MSW stream (30.65, 9.948 and 5.649 kg/tonne of MSW respectively). These types of wastes are mostly discarded into the waste stream after single use only. PET generation rate was found as 7.7 kg/tonne of MSW, which was much more than the national average of India (0.702 kg/tonne of MSW) (CPCB, 2015). Although PET waste generation was more at household level, but due to its high recycling rate and resale value, the amount reaching to the transfer station is eventually lesser than HDPE and LDPE. Generation rate of different types of plastic wastes for the study area along with their possible applications is shown in Table 3. The total generation rate of different types of plastic wastes in the study area was found to be 56.904 kg/tonne of MSW. The results obtained were found to be consistent with the findings of CPCB. The CPCB reported that, Dhanbad generates 50.16 kg of plastic waste per tonne of MSW (CPCB, 2015). A report obtained from DMC revealed that the total MSW generated in the study area was approximately 129 tonne/d (DMC, 2016). Therefore, the total estimated plastic waste generation rate was 7.34 tonne/d, i.e., 5.7% of the total MSW generation which was close to the national average of 6.9% of total MSW (CPCB, 2017). In most of the developing countries, the composition of plastic waste varies from 5 to 8% of the total MSW (Thanh et al., 2010). A personal interview conducted with the active scrap dealers in the study area revealed that approximately 4 tonne/d of plastic waste (~55% of total generated plastic waste) is recovered by the informal recycler and rest goes to the dumpsites or remains unattended. Previous studies reported that 50–70% of the generated plastic waste is recovered by informal sector (Das and Tiwari, 2018; Nandy et al., 2015).

4.6. Recovery of recyclable wastes by the informal sector

The people involved in informal recycling are poor and marginalised groups of the society for whom waste picking is a source of livelihood. For the assessment of waste recovery scenario, a questionnaire guided interview was carried out with the involved waste pickers or scavengers, IWB's and scrap dealers of the study area. Fig. 7 shows the amount (% by weight) of recyclable wastes recovered by the involved recyclers of the study area. It was found that plastic waste recovery rate was maximum (43%) out of the total recyclable waste, while paper & cardboard, metals, glass and others (textile, rubber and leather) had recovery percentage of 27%, 7%, 6% and 17% respectively. Rigamonti et al. (2014) reported that PET, HDPE and LDPE have better recycling potential, whereas other plastic types are mostly non-recyclable. In the present study area, these plastic waste components (PET, HDPE and LDPE) account for approximately 85% of the total plastic waste and thus the waste pickers and IWB's are attracted for collection as they have high resale value.

4.7. Recovery and revenue generation from plastic waste recycling by the informal sector

There is no established data or study which can ascertain the contribution of informal sector in plastic waste collection or recycling for Indian cities. The present study determined the contribution of various actors involved in plastic waste collection, recycling and recovery. Field survey and questionnaire guided personal interviews were used to collect the information related to per day collection of different types of plastic waste by the actors involved in informal recycling. Table 5 shows the average plastic waste collection rate (in kg/d) by waste pickers and IWB's. It was found that average plastic waste collected by a waste picker and an IWB were approximately 19 kg/d and 53 kg/d respectively. The waste picker uses sacks to collect plastic waste from streets, community bins and dumping sites. In the study area, IWB's purchase recyclable plastic waste from households and shops. They use either bicycle or tricycle for plastic waste collection and thus have more collection rate than waste pickers. It has been observed that the waste pickers and IWB's mostly collect PET, HDPE and LDPE that have high resale value in comparison to other plastic wastes. There were two categories of scrap dealers active in the study area: small scrap dealers (average plastic waste collection <500 kg/d) and large scrap dealers (average plastic waste collection >500 kg/d). Waste pickers and IWB's sell their collected plastic waste to the scrap dealers. It was found that on a daily basis average plastic waste bought by small and large scrap dealer was 374 kg/d and 650 kg/d respectively (Table 6).

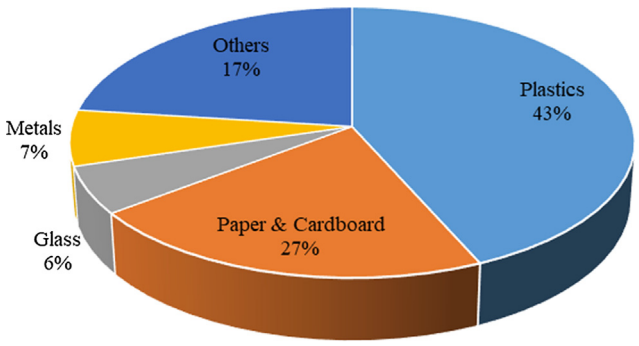

Fig. 7. Percentage distribution of different types of recyclable wastes recovered by informal sectors.

Table 5
Recovery and revenue generation from plastic waste by waste pickers and IWB's.

Types of plastic	Waste picker		IWB	
	Collection (kg/d)	Revenue (US$/d)	Collection (kg/d)	Revenue (US$/d)
PET	7	0.85	19.53	0.91
HDPE	5.32	0.46	14.78	0.69
LDPE	1.71	0.08	4.75	0.12
OTHERS	4.94	0.46	13.73	0.43
Total	19	1.85	52.8	2.15

Table 6
Recovery and revenue generation from plastic waste by scrap dealers.

Types of plastic	Small scrap dealer		Large scrap dealer	
	Collection (kg/d)	Revenue (US$/d)	Collection (kg/d)	Revenue (US$/d)
PET	128	3.90	222	6.77
HDPE	115	3.51	200	6.10
LDPE	42	0.64	73	1.11
PVC	27	0.82	47	1.43
PP	35	0.79	61	1.39
PS	6	0.09	11	0.17
PC, PU	21	0.64	36	1.10
Total	374	10.39	650	18.07

A high variation in revenue generation from plastic waste recovery was observed for the waste pickers, IWB's and scrap dealers (Tables 5 and 6). The revenue generation from plastic waste recovery depends on the types of plastic wastes and their market demand. For e.g., PET and HDPE plastics have more resale value due to better recycling efficiency. Therefore, their collection rate was also more in comparison to other types of plastic wastes. It can be seen from Table 5 that, a waste picker recovers US$ 0.85 and US$ 0.46 per day, whereas IWB recovers US$ 0.91 and US$ 0.61 per day from recycling of PET and HDPE plastic waste respectively. The other types of plastic wastes (such as PVC, PP, PS, PU and PC) have less recycling rate and resale value. A waste picker and an IWB recover US$ 0.46 and US$ 0.43 per day respectively from recycling of other types of plastic wastes. On an average, waste picker and IWB recover US$ 1.85 and US$ 2.15 per day respectively from all types of plastic waste recycling in the study area. IWB collects approximately three times more plastic waste than waste picker, however the effective revenue recovery was not so high with compared to waste picker (Table 5), because IWB's work on business model in which they purchase plastic waste from households and shops and then sell it to the scrap dealers with a very low profit margin. But, the effective income of IWB's was higher than waste pickers, as they also collect other types of recyclable wastes (paper, cardboard, metals and glass). The waste pickers in the study area claimed that their already deplorable condition becomes worse during extreme weather condition and due to stray animals. The waste pickers in the study area make least profit out of all the various types of informal actors (which is consistent with Zia and Devadas, 2007).

Scrap dealers also work on the business model in which bought plastic waste from waste pickers and IWB's are processed (segregation and compaction) and sold to the industries involved in plastic waste recycling. There are two types of scrap dealers (small and large) active in the study area. Most of the times, small scrap dealers sell their collected plastic waste to the large scrap dealers. Table 6 shows the daily average plastic waste collection and revenue generation by small and large scrap dealers. Again PET and HDPE were the most sought plastic wastes. The revenue generated from PET and HDPE by small scrap dealer was US$ 3.90 and US$ 3.51 per day respectively, whereas by large scrap dealer, it was US$ 6.77 and US$ 6.10 per day respectively. On a daily average basis, small scrap dealer and large scrap dealer recover US$ 10.39 and US$ 18.07 per day respectively from plastic waste recycling.

5. Conclusions

- Generally, houses in the cities of developing countries are found in the cluster of similar socioeconomic groups. The information of composition of plastic waste generated by different socioeconomic groups could be combined with the current status of plastic waste recycling by informal sectors to support the authorities and decision makers in developing effective plastic waste recycling and disposal mechanism.
- In this study, three different socioeconomic groups, namely higher socioeconomic group (HSEG), middle socioeconomic group (MSEG) and lower socioeconomic group (LSEG) were identified. The plastic waste generation rates for HSEG, MSEG and LSEG were 51 g/c/d, 27 g/c/d and 8 g/c/d respectively. The generation rate of polyethylene terephthalate (PET) and high density polyethylene (HDPE) was found to be maximum in the households of all the socioeconomic groups.
- Three non-linear machine learning models (artificial neural network (ANN), support vector machine (SVM) and random forest (RF)) were developed and compared for the prediction accuracy of plastic waste generation rate using pre-selected socioeconomic variables. It was observed that ANN performed best.
- Currently, recovery of the generated plastic waste in the study area is carried out informally by the people such as waste pickers, itinerant waste buyers (IWB's) and scrap dealers. On an average, a waste picker, an IWB, a small and large scrap dealer recover 19, 53, 374 and 650 kg/d of plastic waste respectively and generate US$ 1.85, US$ 2.15, US$ 10.39 and US$ 18.07 per day respectively from selling of the recovered plastic waste. All the actors involved recover maximum revenue form recycling of PET and HDPE types of plastic waste, because these two have maximum recycling potential.
- Knowledge of quantity and composition of plastic waste generated are essential for efficient plastic waste management. The study will help the stake holders (municipal authorities, policy

makers, public and private sectors) to understand the dynamics of plastic waste generation and to identify the potential of plastic waste recycling which will not only reduce the burden of landfilling, but also enhance the revenue generation by augmenting the informal recycling into formal one.

Acknowledgements

The authors acknowledge the support provided by the Department of Environmental Science & Engineering, Indian Institute of Technology (Indian School of Mines), Dhanbad, India for carrying out the research work. The authors also acknowledge the support provided by the officials of Dhanbad Municipal Corporation, India.

References

A.S.T.M. D5231-92, 2008. Standard Test Method for Determination of Composition of Unprocessed Municipal Solid Waste. ASTM International, West Conshohocken (PA).

Abbasi, M., El Hanandeh, A., 2016. Forecasting municipal solid waste generation using artificial intelligence modelling approaches. Waste Manage. (Oxford) 56, 13–22.

Abbasi, M., Abduli, M.A., Omidvar, B., Baghvand, A., 2013. Forecasting municipal solid waste generation by hybrid support vector machine and partial least square model. Int. J. Environ. Res. 7 (1), 27–38.

Abdoli, M.A., Nezhad, M.F., Sede, R.S., Behboudian, S., 2012. Longterm forecasting of solid waste generation by the artificial neural networks. Environ. Prog. Sustain. Energy 31 (4), 628–636.

Al-Khatib, I.A., Hammad, A.A., Sharkas, O.A., Sato, C., 2015. Public concerns about and perceptions of solid waste dump sites and selection of sanitary landfill sites in the West Bank, Palestinian territory. Environ. Mon. Assess. 187 (4), 186.

Azadi, S., Karimi-Jashni, A., 2016. Verifying the performance of artificial neural network and multiple linear regression in predicting the mean seasonal municipal solid waste generation rate: a case study of Fars province, Iran. Waste Manage. 48, 14–23.

Beigl, P., Lebersorger, S., Salhofer, S., 2008. Modelling municipal solid waste generation: a review. Waste Manage. (Oxford) 28 (1), 200–214.

British Plastic Federation (BPF), 2012. Plastic Industry in India: A BPF Overview. <http://www.bpf.co.uk/article/the-plastics-industry-in-india-an-overview-446.aspx> (accessed on 16.11.2017).

Central Pollution Control Board (CPCB), 2015. Assessment & Quantification of Plastics Waste Generation in Major Cities. Ministry of Environment Forest and Climate Change (MoEFCC). <http://cpcb.nic.in/PW-Report-2015.pdf> (accessed 02.12.2017).

Central Pollution Control Board (CPCB), 2017. Capacity Building Program on Implementation of Waste Management Rules, 2016. Tool Kit on Plastic Waste Management Rules 2016. <http://www.npcindia.gov.in/wp-content/uploads/2017/08/Tool-kit-on-Plastic-Waste-Management-Rules-2016.pdf> (accessed 20.07.2018).

Chung, S.S., 2010. Projecting municipal solid waste: the case of Hong Kong SAR. Resour. Conserv. Recycl. 54 (11), 759–768.

Das, P., Tiwari, P., 2018. Valorization of packaging plastic waste by slow pyrolysis. Resour. Conserv. Recycl. 128, 69–77.

DMC, 2016. Dhanbad Municipal Corporation. Development, Operation and Management of Municipal Solid Waste (MSW) Collection, Transportation, Processing and Landfill Facility for Dhanbad City. Unpublished report, Dhanbad, India.

Dyson, B., Chang, N.B., 2005. Forecasting municipal solid waste generation in a fast-growing urban region with system dynamics modeling. Waste Manage. (Oxford) 25 (7), 669–679.

Emery, A.D., Griffiths, A.J., Williams, K.P., 2003. An in depth study of the effects of socio-economic conditions on household waste recycling practices. Waste Manage. Res. 21 (3), 180–190.

Goel, S., Ranjan, V.P., Bardhan, B., Hazra, T., 2017. Forecasting Solid Waste Generation Rates. Modelling Trends in Solid and Hazardous Waste Management, 35–64.

Census of India, 2011. Office of the Registrar General & Census Commissioner, India. Government of India. <http://www.censusindia.gov.in/2011census/population_enumeration.html> (accessed on 21.11.2017).

Kannangara, M., Dua, R., Ahmadi, L., Bensebaa, F., 2018. Modeling and prediction of regional municipal solid waste generation and diversion in Canada using machine learning approaches. Waste Manage. (Oxford) 74, 3–15.

Khan, D., Kumar, A., Samadder, S.R., 2016. Impact of socioeconomic status on municipal solid waste generation rate. Waste Manage. (Oxford) 49, 15–25.

Khan, S., Faroqi, I.H., 2012. Prioritising municipal solid waste management factors in India using fuzzy analytic hierarchy process. Int. J. Environ. Waste Manage. 10 (4), 423–440.

Kumar, A., Samadder, S.R., 2017. An empirical model for prediction of household solid waste generation rate–A case study of Dhanbad, India. Waste Manage. (Oxford) 68, 3–15.

Mac Berthouex, P., Brown, L.C., 2002. Statistics for Environmental Engineers. Lewis Publishers, USA.

MoEFCC, 2016. Plastic waste management rules, 2016. Ministry of Environment Forest and Climate Change (MoEFCC), Government of India. <http://www.moef.gov.in/sites/default/files/PWM%20Rules%2C%202016.pdf> (accessed on 08.05.2018).

Monavari, S.M., Omrani, G.A., Karbassi, A., Raof, F.F., 2012. The effects of socioeconomic parameters on household solid-waste generation and composition in developing countries (a case study: Ahvaz, Iran). Environ. Monit. Assess. 184 (4), 1841–1846.

Nandy, B., Sharma, G., Garg, S., Kumari, S., George, T., Sunanda, Y., Sinha, B., 2015. Recovery of consumer waste in India–A mass flow analysis for paper, plastic and glass and the contribution of households and the informal sector. Resour. Conserv. Recycl. 101, 167–181.

Nzeadibe, T.C., 2009. Solid waste reforms and informal recycling in Enugu urban area. Nigeria. Habitat International 33 (1), 93–99.

Pew Research Center, 2014. Social & Demographic Trends. Income range for middle-income households and households in other income tiers. <http://www.pewsocialtrends.org/2015/12/09/the-american-middle-class-is-losing-ground/st_2015-12-09_middle-class-10/> (accessed 30.11.2017).

Purcell, M., Magette, W.L., 2009. Prediction of household and commercial BMW generation according to socio-economic and other factors for the Dublin region. Waste Manage. (Oxford) 29 (4), 1237–1250.

Ramachandra, T.V., Bharath, H.A., Kulkarni, G., Han, S.S., 2018. Municipal solid waste: generation, composition and GHG emissions in Bangalore, India. Renew. Sustain. Energy Rev. 82, 1122–1136.

Rigamonti, L., Grosso, M., Møller, J., Sanchez, V.M., Magnani, S., Christensen, T.H., 2014. Environmental evaluation of plastic waste management scenarios. Resour. Conserv. Recycl. 85, 42–53.

Sembiring, E., Nitivattananon, V., 2010. Sustainable solid waste management toward an inclusive society: Integration of the informal sector. Resour. Conserv. Recycl. 54 (11), 802–809.

Sidique, S.F., Lupi, F., Joshi, S.V., 2010. The effects of behavior and attitudes on drop-off recycling activities. Resour. Conserv. Recycl. 54 (3), 163–170.

Singh, N., Hui, D., Singh, R., Ahuja, I.P.S., Feo, L., Fraternali, F., 2017. Recycling of plastic solid waste: a state of art review and future applications. Compos. B Eng. 115, 409–422.

Thanh, N.P., Matsui, Y., Fujiwara, T., 2010. Household solid waste generation and characteristic in a Mekong Delta city, Vietnam. J. Environ. Manage. 91 (11), 2307–2321.

Xiao, L., Lin, T., Chen, S., Zhang, G., Ye, Z., Yu, Z., 2015. Characterizing urban household waste generation and metabolism considering community stratification in a rapid urbanizing area of China. PLoS One 10 (12), 1–16.

Zia, H., Devadas, V., 2007. Municipal solid waste management in Kanpur, India: obstacles and prospects. Manage. Environ. Qual.: Int. J. 18 (1), 89–108.

Zia, H., Devadas, V., Shukla, S., 2008. Assessing informal waste recycling in Kanpur City, India. Manage. Environ. Qual.: Int. J. 19 (5), 597–612.